Sustainable Cities and Society 51 (2019) 101792

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Chance-constrained CAES and DRP scheduling to maximize wind power harvesting in congested transmission systems considering operational flexibility

Arya Abdolahi[a], Farhad Samadi Gazijahani[a], As'ad Alizadeh[b], Navid Taghizadegan Kalantari[a,*]

[a] Department of Electrical Engineering, Azarbaijan Shahid Madani University, Tabriz, Iran
[b] Department of Mechanical Engineering, College of Engineering, University of Zakho, Zakho City, Iraq

ARTICLE INFO

Keywords:
Congestion management
Demand response
Energy storage
Wind energy
Uncertainty

ABSTRACT

As enlarging share of renewables brings up a promising future for clean power generation, nonetheless, it imposes new challenges into the secure operation of power systems such occurrence of distasteful congestion, discriminatory locational marginal pricing (LMP) and also increasing uncertainty and inflexibility. To address these issues, a novel chance constrained two-stage programming is developed, where in the first stage social welfare of system is maximised while in the second stage a stochastic security constrained unit commitment problem is executed along with compressed air energy storage (CAES) and demand response program (DRP) to minimize both operation costs and wind curtailment. Both DRP and CAES are cooperatively applied to maximize wind proliferation and social welfare, alleviate the congestion of network, smooth LMP at different nodes, and improve technical characterizations of system. The problem is formulated as an exact mixed integer non-linear programming (MINLP) considering operational flexibility by means of power capacity for up/down power regulation and then is solved using primal-dual interior point solver. Finally, a case study based on modified IEEE 30-bus transmission system with three zones is performed and the results are duly expressed and analysed to corroborate the pertinence of the proposed model.

1. Introduction

1.1. Concept and motivation

The generation business is rapidly becoming market-driven. Although system security is still one of the major aspects of the operation of the power system, it cannot be compromised in a market-driven method. Market operators in different independent system operators use standard market design for planning a secure, cost-effective, and reliable generation for the day-ahead power market. One of the main foundations of such market is a security-constrained unit commitment (SCUC), which uses the exact data presented by participants in the power market such as generation unit data, available transfer capability, generation offers, demand bids, scheduled transactions, curtailment contracts, etc. (Gazijahani & Salehi, 2018a; Shafie-Khah, Moghaddam, Sheikh-El-Eslami, & Catalão, 2014). The SCUC provides an effective economic unit commitment (UC) that is possible from the physical viewpoint. The generation dispatch based on SCUC is made available to corresponding market participants. Participants of the power market can utilize available signals for reconsideration of their bids on the generation resources that includes the signal of LMPs and lines congestion (Roscoe & Ault, 2010).

With respect to the high penetration of wind powers in electricity markets, these inexhaustible resources play a significant role in stable and clean energy delivery. Regarding uncertain and non-dispatchable features of the wind power resources, the system operators face with new challenges such as unbalancing between required load demand and wind power generation, voltage stability, increasing diversity on the supply side and consequently necessity of more flexibility (Heydarian-Forushani, Golshan, & Moghaddam, 2015; Shafie-Khah, Moghaddam, & Sheikh-El-Eslami, 2011; Yang et al., 2016). In the presence of these kinds of challenges, high penetration of wind power resources could be caused by serious dangers in the control and operation of the power systems. Due to these effects, there is an essential need for greater flexibility in terms of power system operation in order to capable to reduce undesirable effects of uncertainties of wind power generation.

* Corresponding author.
E-mail addresses: a.abdollahi@azaruniv.ac.ir (A. Abdolahi), f.samadi@azaruniv.ac.ir (F.S. Gazijahani), asad.alizadeh2010@gmail.com (A. Alizadeh), taghizadegan@azaruniv.ac.ir (N.T. Kalantari).

https://doi.org/10.1016/j.scs.2019.101792
Received 1 May 2019; Received in revised form 8 July 2019; Accepted 17 August 2019
Available online 19 August 2019

Nomenclature

A. Sets and indices

N_S	Set of scenarios
N_B	Set of buses
N_T	Set of hours
N_G	Set of generators
N_W	Set of wind power units
N_{CAES}	Set of CAES units
N_L	Set of lines
S	Index of scenarios
b	Index of busses
t	Index of hours
i	Index of unit
w	Index of wind power units
k	Index of CAES units
l	Index of lines
FT	Index of fuel limits

B. Variables

$p_{s,t,i}^{Gen}$	Generated power of *i*th unit at time *t* and scenario *s*
$p_{s,t,w}^{Wind}$	Generated power of *w*th wind power unit at time *t* in scenario *s*
$p_{s,t,k}^{Dis}$	Discharged power value of *k*th CAES unit at time *t* in scenario *s*
$p_{s,t,k}^{Ch}$	Charged power value of *k*th CAES unit at time *t* and scenario *s*
$p_{s,t,k}^{CAES}$	Generated power of *k*th CAES at time *t* and scenario *s*
$p_{s,b,t}^{D}$	Demand value of *b*th bus at time *t* in scenario *s*
$LMP_{s,b,t}$	Locational marginal price of *b*th bus at time *t* and scenario *s*
$p_{s,b}^{Net}$	Net active power of *b*th bus at time *t* and scenario *s*
$q_{s,b}^{Net}$	Net reactive power of *b*th bus at time *t* and scenario *s*
$v_{s,b}$	Voltage magnitude of *b*th bus at time *t* and scenario *s*
δ_b	Voltage angle of *b*th bus at time *t* in scenario *s*
$i_{s,l}$	Electric current of *l*th line at time *t* and scenario *s*
$p_{s,b}$	Active power of *b*th bus in scenario *s*
$q_{s,b}$	Reactive power of *b*th bus in scenario *s*
$p_{s,t,l}^{Loss}$	Power losses of *l*th line at time *t* in scenario *s*
$g_{s,t,i}$	Commitment status of unit *i* at time *t* scenario *s*
$sr_{s,t,i}$	Spinning reserve of unit *i* at time *t* in scenario *s*
$nr_{s,t,i}$	Non-spinning reserve of unit *i* at time *t* in scenario *s*
$ru_{s,t,i}$	Regulation up of unit *i* at time *t* and scenario *s*
$rd_{s,t,i}$	Regulation down of unit *i* at time *t* scenario *s*
$p_{s,t,l}^{flow}$	Active power flow of line *l* at time *t* scenario *s*
$\upsilon_{s,t,k}^{w}$	Value of released air of *k*th CAES unit at time *t* and scenario *s*
$\upsilon_{s,t,k}^{inj}$	Value of injected air of *k*th CAES unit at time *t* and scenario *s*
$a_{s,t,k}$	Inventory level of *k*th CAES unit at time *t* in scenario *s*
$SoC_{s,t,k}$	State of charge of *k*th CAES unit at time *t* in scenario *s*
d_t^0	Initial load demand at time t
d_t	Load demand after implementing demand response at time *t*
ρ_t^0	Initial electricity price at time *t*
ρ_t	Electricity price at time *t*

C. Functions

$F(x)$	Objective function value
$Z(x, \xi)$	Constraint function value
F_i^C	Generation cost function of unit i
C_{DR}	Cost of DRP implementation
F_f	First-stage objective function
F_s	Second-stage objective function
B	Benefit function
NP	Net profit
Φ	Equality constraints
Ψ	Inequality constraints

D. Parameters

G,B	Conductance and susceptance of lines
R,X	Resistance and reactance of lines
$P_w^{Wind,min}$	Minimum power generated by *w*th wind turbine
$P_w^{Wind,max}$	Maximum power generated by *w*th wind turbine
Prob{}	Probability of the event{}
X	Deterministic possible zone
K^{Wind}	Operation cost coefficient of wind turbines
K^{Loss}	Cost of losses
$SUC_{s,t,i}$	Start-up cost
$SDC_{s,t,i}$	Shut down cost
R_t^S	System spinning reserve requirement
R_t^N	System non-spinning reserve requirement
R_t^{ru}	System regulation up requirement
R_t^{rd}	System regulation down requirement
P_i^{min}, P_i^{max}	Minimum and maximum active power of *i*th unit
RU_i, RD_i	Ramping up/down limit of *i*th unit
UT_i, DT_i	Number of hours a unit require to remain on/off at the beginning of the scheduling period
TU_i, TD_i	Number of hours a unit has been on/off at the beginning of the scheduling period
MU_i, MD_i	Minimum up/down time of *i*th unit
Q_i^{min}, Q_i^{max}	Minimum and maximum reactive power of *i*th unit
$F_{FT}^{min}, F_{FT}^{max}$	Minimum and maximum fuel consumption limit of fuel type *FT*
$P_l^{flow,min,max}$	Minimum and maximum power flow limit of lines
V_b^{min}, V_b^{max}	Minimum and maximum voltage magnitude of buses
A_k^{min}, A_k^{max}	Minimum and maximum capacity of *k*th CAES unit
$SoC_k^{min,max}$	Minimum and maximum SoC of *k*th CAES unit
E	Elasticity in the price elasticity matrix
η^{Ch}, η^{Dis}	Charging and discharging efficiency of CAES units
Γ_k^w	Efficiency factor of CAES for generating power
	Efficiency factor of CAES for injecting air
$N_k^{w,min,max}$	Minimum and maximum value of released air of *k*th CAES unit
$N_k^{inj,min,max}$	Minimum and maximum value of injected air of *k*th CAES unit
ρ_s	Weight of scenario s
λ	Lagrangian multiplier of equality constraint
μ	Lagrangian multiplier of inequality constraint

E. Abbreviations

SCUC	Security constrained unit commitment
DRP	Demand response program
ESS	Energy storage system
CM	Congestion management
ATC	Available transfer capability
CAES	Compressed air energy storage
MG	Microgrid
LMP	Locational marginal price
RTP	Real time pricing
GENCOs	Generation companies
CCP	Chance constrained programming
MINLP	Mixed integer non-linear programming
UC	Unit commitment
FACTS	Flexible AC transmission systems
WT	Wind turbine
OPF	Optimal power flow

The observed variability and uncertainty of wind power have highlighted the need for the use of flexible resources as a means to integrate increased levels of wind power. The energy storage system (ESS) and demand response (DR) are the two flexible sources that are often identified as being compatible with wind power. Both of these source types have been known as an effective means to meet many of the challenges associated with wind power integration (Nikoobakht & Aghaei, 2016).

One of the main problems in the transmission networks operation in the presence of wind power sources is that several lines will not have sufficient capacity to transmit the power, which is contracted in the day-ahead power market. Therefore, the lines that have not enough capacity to transmit the power called congestion. On the other hand, congestion is defined as a situation of overloading of network lines. The created congestion surplus in the power system changes LMPs and dissatisfaction with customers (Abdolahi et al., 2018; Conejo, Milano, & García-Bertrand, 2006; Hazra & Sinha, 2007; Salehizadeh, Rahimi-Kian, & Oloomi-Buygi, 2015; Yousefi, Nguyen, Zareipour, & Malik, 2012). One of the solution to deal with this problem is to utilize ESS and DRP as flexible sources. In addition to undeniable benefits of ESSs, the ESS changes some technical constraints like the change in the voltage stability margin, which plays an important role in the system security (Aghaei, Alizadeh, Abdollahi, & Barani, 2016; Kargarian, Raoofat, & Mohammadi, 2011). In this paper, both ESS and DRP used as a reserve source to reduce the uncertainty of renewables, control the fluctuation of wind power production, increase the penetration of wind powers, maximize social welfare and manage the congestion of lines in the transmission network (Zhao, Wang, Watson, & Guan, 2013). The DRP encourages customers to regulate their consumption voluntarily based on price signals (Wang, Wang, & Guan, 2013) and also DRP determines curtailed and shifted load amount (Khodaei, Shahidehpour, & Bahramirad, 2011).

1.2. Literature review

Several methods have been used for congestion management (CM) in the prior literature (Dehnavi & Abdi, 2017; Kumar, Srivastava, & Singh, 2005; Liu, Wu, Wen, & Østergaard, 2014; Moradi, Reisi, & Hosseinian, 2018; Yousefi, Nguyen, Zareipour, & Malik, 2012; Zaeim-Kohan, Razmi, & Doagou-Mojarrad, 2018). For example, DRP has been performed collaboratively with the retail electricity market in order to reduce the congestion of the suggested national grid (Moradi et al., 2018). Authors in ref. Yousefi et al. (2012b) proposed both DRP and flexible AC transmission systems (FACTS) controllers to managing congestion in the minimum operation cost. A distribution congestion price-based market mechanism is presented in (Liu et al., 2014) to influence the behaviour of DRP for CM in the active distribution networks in the day-ahead electricity market. DRP is proposed based on power transfer distribution factors, available transfer capability (ATC), and dynamic DC optimal power flow to alleviate congestion of lines, increase ATC index and improve the reliability of the system (Dehnavi & Abdi, 2017). The paper (Zaeim-Kohan et al., 2018) focuses on solving CM problem with heuristic optimization algorithm as well as considering generation rescheduling, emergency DRP and direct load control during congested hours.

In the previous study, a two-stage robust SCUC problem has been suggested to manage the uncertainty of wind power output in the power system scheduling (Shao, Wang, Shahidehpour, Wang, & Wang, 2017). A model proposed in (Tejada-Arango, Sánchez-Martın, & Ramos, 2018) for the SCUC using the line outage distribution factors. The author in (Fernández-Blanco, Dvorkin, & Ortega-Vazquez, 2017) introduced a multi-stage formulation of SCUC with generation and transmission contingency in addition of wind power uncertainty. A stochastic model of SCUC combine with compressed air energy storage (CAES) and wind power production as well as static voltage stability analysis has been discussed in (Ghaljehei et al., 2018). A comprehensive study of stochastic security-constrained hydrothermal unit commitment has been presented in (Ansari, Amjady, & Vatani, 2014).

Information gap decision theory model has been employed in (Shafiee, Zareipour, Knight, Amjady, & Mohammadi-Ivatloo, 2017) for modelling price uncertainties with risk constrained biding/offering strategy for CAES. The author suggested an adaptive robust self-scheduling model for a wind producer-CAES describing the wind output and price uncertainties (Attarha, Amjady, Dehghan, & Vatani, 2018). This paper applies a decomposable bi-level method to solve the problem. The work in (Cleary, Duffy, OConnor, Conlon, & Fthenakis, 2015) is estimated the amount of wind curtailment on 2020 All Island of Ireland system for different scenarios contain with and without CAES. In Ref. Gazijahani and Salehi (2018b), comprehensive work has been performed associated with the planning of microgrids (MGs) considering DRP apply an innovative robust optimization method. Incentive-based DRP with dynamic reconfiguration scheduling for optimal operation of MGs using Hong's point estimate approach discussed in (Seyyedeh-Barhagh, Majidi, Nojavan, & Zare, 2019). The study in (Zhang et al., 2018) designed a two-stage load planning with incentive-based DRP for end consumers.

1.3. Novelties and contribution

Pursuant to our scientific knowledge, there are multiple shortcomings in the previous works that should be addressed properly:

a) They have mainly focused on congestion alleviation by applying a unique action (like FACTS devices or generator rescheduling) and the impact of new technologies such as CAES and DRP on the congestion and subsequently social welfare of system is not investigated extensively.
b) The joint optimization of CAES charging scheduling and DRP with spatial distribution has not been reported so far in the literature.
c) The previous works have not considered the maximization of wind power harvesting within the congestion management problem. Furthermore, an effective operational flexibility measure should be developed to increase the wind power accommodation in the congested transmission systems, where this issue has not been studied.
d) Besides, the uncertainty related to wind generation should be incorporated into the congestion management problem by an appropriate instrument while the prior technical references have mostly ignored this important issue

To fill out these gaps, this paper proposes a two-stage approach, in which at the first stage the social welfare problem, which is the difference between the cost of consumers and profit of producers, will be maximized. In doing so, locational marginal pricing (LMP) method is applied as a signal to alleviate congestion induced by wind powers. In this stage, LMP will be found by solving the social welfare optimization problem and alleviate the congestion of the transmission system with the goal of maximizing wind power harvesting. Then, at the second stage, the stochastic SCUC model considering DRP is run to reduce the wind power curtailment and accommodate high penetration of wind power into the system with the goal of minimizing the operation cost of the whole system. Due to the discussion mentioned above, the main novelties of this article can be summarized as follow:

- Developing a computational efficient stochastic two-stage model for CM and LMP smoothing in the wind-integrated transmission systems.
- Applying an integrated CAES and DR scheduling to maximize social welfare and wind power harvesting in the congested network.
- Considering the operational flexibility of the system by means of power capacity for up/down power regulation.
- Utilization of an innovative chance-constrained approach to tackle the uncertainty of wind generation and its associated risk.

1.4. Paper organization

The paper is organized as follows. The co-optimization approach is given in Section 2. In Section 3, the problem statement and proposed methodology are presented. Stochastic chance constrained programming is introduced in Section 4. Case study and simulation results are provided in Section 5 and finally, the conclusion are discussed in Section 6.

2. Co-optimization approach

2.1. Concept of DRP

The DRPs are one of the important tools of the system in the restructured environment, which are described as a change in electricity consumption by end-users from their normal consumption schema in response to change in electricity price during the time. As other definition of DRPs, they are designed incentive payments in order to create minimum electricity consumption when the wholesale electricity market price is high or the reliability of the system compromised (Aazami, Aflaki, & Haghifam, 2011). On the other word, the DRPs be able to change the value and time of electricity consumption until the best efficiency of consumption done over the peak hours (Seyyedeh-Barhagh et al., 2019). Due to different energy tariffs in the various periods, the consumers have been encouraged to manage their consumption with the goal of reducing their costs. Therefore, with using the DR sources, there is no need for installation of new distributed generation units for the certain period. The DRPs can reduce investment costs of the transmission network, prevent of lines to work with maximum capacity aim to manage congestion and ameliorate reliability when a contingency occurs in the network (Abdolahi et al., 2018).

DRPs can be divided into two major categories with the name of incentive-based programs and time-based programs (Gazijahani & Salehi, 2018c). In this paper, an efficiency time-based program with the name of real time pricing (RTP) introduced to reduce the load consumption in peak hour's aim to congestion management in transmission network and reduce the cost of consumers in order to maximize social welfare as well as alleviate operation costs of the proposed network (Seyyedeh-Barhagh et al., 2019). According to the RTP, some percentage of inessential consumptions in peak hours with high tariffs must be transferred to the off-peak hours with lower tariff up to flatten load curve. Therefore, according to the mentioned explanations, the new load profile will be presented with considering DRPs for the transmission network. To show the load sensitivity to the energy price, demand elasticity must be specified that can be described as the ratio of load change to the price change in Eq. (1).

Elasticity includes two parts of self-elasticity and cross elasticity. Self-elasticity illustrated the load sensitivity at tth hour to the price variation at tth hour and cross-elasticity expressed the load sensitivity at tth hour to the price variation at tth hour, which are negative and positive amounts, respectively. If demand variation is larger than price variation, the demand is elastic (Nikoobakht et al., 2018). Elasticity is the sensitivity of demand to price, as shown in Eqs. (1) and (2).

$$E_{t,t'} = \frac{\rho_{t'}^0}{d_t^0} \times \frac{\partial d_t}{\partial \rho_{t'}} \tag{1}$$

$$\begin{cases} E_{t,t'} \le 0, \; if \to t = t' \\ E_{t,t'} \ge 0, \; if \to t \ne t' \end{cases} \tag{2}$$

The amount of self and cross elasticity depicted in Eq. (3) as a 24*24 matrix for a day that is called price elasticity matrix (PEM):

$$\begin{bmatrix} \Delta d_1/d_1^0 \\ \Delta d_2/d_2^0 \\ \Delta d_3/d_3^0 \\ \vdots \\ \Delta d_{24}/d_{24}^0 \end{bmatrix} = \begin{bmatrix} E_{1,1} & \cdots & E_{1,24} \\ \vdots & \ddots & \vdots \\ E_{24,1} & \cdots & E_{24,24} \end{bmatrix} \times \begin{bmatrix} \Delta\rho_1/\rho_1^0 \\ \Delta\rho_2/\rho_2^0 \\ \Delta\rho_3/\rho_3^0 \\ \vdots \\ \Delta\rho_{24}/\rho_{24}^0 \end{bmatrix} \tag{3}$$

The consumer's net profit is shown in Eq. (4)

$$NP(d_t) = Ben(d_t) - [d_t \times \rho_t] \tag{4}$$

To maximize the customer's benefit, the derivation of the Eq. (4) must be zero as (5). Taylor series of Benefit (B) is as (6) that is a quadratic equation.

$$\frac{\partial NP(d_t)}{\partial d_t} = \frac{\partial \text{Ben}(d_t)}{\partial d_t} - \rho_t = 0 \to \frac{\partial \text{Ben}(d_t)}{\partial d_t} = \rho_t \tag{5}$$

$$\text{Ben}(d_t) = \left\{ \text{Ben}(d_t^0) + \frac{\partial \text{Ben}(d_t^0)}{\partial d_t}[d_t - d_t^0] + \frac{1}{2}\frac{\partial^2 \text{Ben}(d_t^0)}{\partial d_t^2}[d_t - d_t^0]^2 \right\} \tag{6}$$

With achieving optimal consumption; customers can maximize their profits as Eq. (7).

$$\text{Ben}(d_t) = \left\{ \text{Ben}(d_t^0) + \rho_t^0 [d_t - d_t^0] + \frac{1}{2}\frac{\rho_t^0}{E_{t,t} d_t^0}[d_t - d_t^0]^2 \right\} \tag{7}$$

The differential of Eq. (7) is obtained as Eq. (8), which represents the price of energy per hour.

$$\frac{\partial \text{Ben}(d_t)}{\partial d_t} = \rho_t^0 \left\{ 1 + \frac{d_t - d_t^0}{E_{t,t} d_t^0} \right\} \tag{8}$$

By combining the Eqs. (5), (8), the single-period responsive load model is given as follows.

$$d_t = d_t^0 \left\{ 1 + \frac{E_{t,t}[\rho_t - \rho_t^0]}{\rho_t^0} \right\} \tag{9}$$

Multi-period model of the responsive load:

$$d_t = d_t^0 + \sum_{\substack{t=1 \\ t' \ne t}}^{24} E_{t,t'} \times \frac{d_t^0}{\rho_{t'}^0} \times [\rho_{t'} - \rho_{t'}^0] \tag{10}$$

Finally, the completed model of the DRP is a combination of multi-period and single-period models of responsive loads.

$$d_t = d_t^0 \left\{ 1 + E_{t,t}\frac{[\rho_t - \rho_t^0]}{\rho_t^0} + \sum_{\substack{t=1 \\ t' \ne t}}^{24} E_{t,t'}\frac{[\rho_{t'} - \rho_{t'}^0]}{\rho_{t'}^0} \right\} \tag{11}$$

2.2. CAES system

The CAES is a type of energy storage technology that has been invented about 30 years ago with a number of successful facilities in the world. The CAES technology will be explained in multi-steps briefly. At first step, the CAES apply low-cost off-peak energy to store air into underground salt caverns using a motor connected to a compressor. Then energy is retaken after the expansion of the compressed air via a high-pressure air turbine. During the procedure, natural gas is mixed with the air and in the last step; the mixture is fired in a low-pressure natural gas turbine. To improve the system efficiency, waste heat is used to preheat the turbine inlet air by a heat exchanger. Generic capacities for a CAES system are less than 100 MW. The storage period is the longest because its losses are very small.

As a result, the CAES can work in three separate modes (Dash et al., 2019).

- Charging mode: when system load demand is low, then electricity is applied to compress air into an underground storage cavern (the CAES acts like a compressor).
- Discharging mode: when electricity is needed, the compressed air is returned to the surface, heated by natural gas and run through a turbine to sell the produced electrical power to the market (the CAES acts like a generator).
- Simple cycle mode: the CAES just use natural gas to generate

electricity power.

To include all the modes mentioned in our model, the following integer variables and constraints are introduced (Lund & Salgi, 2009).

$$g_{s,t,k} + g^{c}_{s,t,k} \leq 1, \forall\, k, \forall\, t, \forall\, s \tag{12}$$

Eq. (13) shows the linear relation between the volume of released air from storage and the amount of power production by CAES unit. Inventory level calculation is indicated in Eq. (16). The upper and lower production capacity limit of CAES units is presented in constraint (17). Eqs. (18), (19) show the CAES units state of charge and their limitation, respectively.

$$p^{\mathrm{CAES}}_{s,t,k} = (\Gamma^{\mathrm{w}}_{k}.\ \upsilon^{\mathrm{w}}_{s,t,k}) - (\Gamma^{\mathrm{inj}}_{k}.\ \upsilon^{\mathrm{inj}}_{s,t,k}),\ \ \forall\, k, \forall\, t, \forall\, s \tag{13}$$

$$N^{\mathrm{w,min}}_{k}.\ g_{s,t,k} \leq \upsilon^{\mathrm{w}}_{s,t,k} \leq N^{\mathrm{w,max}}_{k}.\ g_{s,t,k},\ \ \forall\, k, \forall\, t, \forall\, s \tag{14}$$

$$N^{\mathrm{inj,min}}_{k}.\ g^{c}_{s,t,k} \leq \upsilon^{\mathrm{inj}}_{s,t,k} \leq N^{\mathrm{inj,max}}_{k}.\ g^{c}_{s,t,k},\ \ \forall\, k, \forall\, t, \forall\, s \tag{15}$$

$$a_{s,t+1,k} = a_{s,t,k} + \upsilon^{\mathrm{inj}}_{s,t,k} - \upsilon^{\mathrm{w}}_{s,t,k}, \forall\, k, \forall\, t, \forall\, s \tag{16}$$

$$\mathrm{A}^{\mathrm{min}}_{k} \leq a_{s,t,k} \leq \mathrm{A}^{\mathrm{max}}_{k}, \forall\, k, \forall\, t, \forall\, s \tag{17}$$

$$SoC_{s,t+1,k} = SoC_{s,t,k} + (p^{\mathrm{Ch}}_{s,t,k}.\ \eta^{\mathrm{Ch}} - p^{\mathrm{Dis}}_{s,t,k}/\eta^{\mathrm{Dis}}) \tag{18}$$

$$\mathrm{SoC}^{\mathrm{min}}_{k} \leq SoC_{s,t,k} \leq \mathrm{SoC}^{\mathrm{max}}_{k}, \forall\, s, \forall\, k, \forall\, t \tag{19}$$

3. Problem formulation

3.1. LMP concept

The LMP, one of the market pricing methods, manages the transmission system efficiently when congestion occurs in a large-scale network. With LMP, participants in the market will know the price of hundreds of places on the system. The following results are obtained from these prices:

- Determining a new position for generation.
- Upgrade transfer in transmission lines.
- Increasing competition in the electricity market.
- Improve the system's ability to meet energy demand.

LMP is the Lagrangian multipliers that are dependent on the active power of any busses. LMP at any node in the system is the dual variable for the equality constraint at that node. According to the spot value of active power in the bth bus, LMP is described as the following equations (Gautam & Mithulananthan, 2007; Wei, Li, & Tomsovic, 2012).

$$\mathrm{LMP}^{\mathrm{Energy}}_{s,b} = \lambda \tag{20}$$

$$\mathrm{LMP}^{\mathrm{Loss}}_{s,b} = \frac{\partial p^{\mathrm{\ Loss}}}{\partial p^{\mathrm{\ Net}}}\lambda \tag{21}$$

$$\mathrm{LMP}^{\mathrm{Congestion}}_{s,b} = \sum_{l=1}^{NL} \mu \frac{\partial p_{l}^{\mathrm{\ Flow}}}{\partial p^{\mathrm{\ Net}}} \tag{22}$$

$$\begin{cases} \mathrm{LMP}^{s,b} = \mathrm{LMP}^{\mathrm{Energy}}_{s,b} + \mathrm{LMP}^{\mathrm{Loss}}_{s,b} + \mathrm{LMP}^{\mathrm{Congestion}}_{s,b} \\ \mathrm{LMP}^{s,b} = \lambda + \lambda\dfrac{\partial p^{\mathrm{\ Loss}}}{\partial p^{\mathrm{Net}}} + \displaystyle\sum_{l=1}^{NL} \mu \frac{\partial p_{l}^{\mathrm{\ Flow}}}{\partial p^{\mathrm{\ Net}}} \end{cases} \tag{23}$$

3.2. First stage (Social welfare maximization)

The main purpose of this stage is to maximize the social welfare of the whole system in the presence of wind energy. The relevant objective function is composed of the producer's net profit and net consumer surplus as depicted in (24).

$$\max \sum_{s=1}^{NS} \sum_{b=1}^{NB} \sum_{t=1}^{NT} \begin{Bmatrix} \displaystyle\sum_{i=1}^{NG} (p^{\mathrm{Gen}}_{s,t,i} \times \mathrm{LMP}_{s,b,t}) + \sum_{w=1}^{NW} (p^{\mathrm{Wind}}_{s,t,w} \times \mathrm{LMP}_{s,b,t}) \\ + \displaystyle\sum_{k=1}^{NCAES} (p^{\mathrm{Dis}}_{s,t,k} \times \mathrm{LMP}_{s,b,t}) \\ - (p^{\mathrm{D}}_{s,b,t} \times \mathrm{LMP}_{s,b,t}) - \displaystyle\sum_{k=1}^{NCAES} (p^{\mathrm{Ch}}_{s,t,k} \times \mathrm{LMP}_{s,b,t}) \end{Bmatrix} \tag{24}$$

Eqs. (25) and (26) show the net active and reactive power of bth bus in each scenario, respectively. The load flow calculation is presented in (27), (28). Also, the power loss of lth line at time t and scenario s is illustrated in (29).

$$p^{\mathrm{\ Net}}_{s,b} = \sum_{b=1}^{NB} \{v_{s,b}\, v_{s,b+1} [\mathrm{G}_{b\ b+1} \cos(\delta_{b} - \delta_{b+1}) + \mathrm{B}_{b\ b+1} \sin(\delta_{b} - \delta_{b+1})]\} \tag{25}$$

$$q^{\mathrm{\ Net}}_{s,b} = \sum_{b=1}^{NB} \{v_{s,b}\, v_{s,b+1} [\mathrm{G}_{b\ b+1} \sin(\delta_{b} - \delta_{b+1}) - \mathrm{B}_{b\ b+1} \cos(\delta_{b} - \delta_{b+1})]\} \tag{26}$$

$$i_{s,l} = (v_{s,b}\measuredangle\delta_{b} - v_{s,b+1}\measuredangle\delta_{b+1})/(\mathrm{R}{+}j\ \mathrm{X}), \forall\, b,\ \forall\, s, \forall\, l \tag{27}$$

$$p_{s,b+1} - \mathrm{j}\, q_{s,b+1} = v^{*}_{s,b+1} i_{s,l}, \forall\, b,\ \forall\, s, \forall\, l \tag{28}$$

$$p^{\mathrm{Loss}}_{s,t,l} = \mathrm{real}(\mathrm{R}(p^{2}_{s,b+1} + q^{2}_{s,b+1})/v^{2}_{s,b+1}), \forall\, s, \forall\, t, \forall\, l \tag{29}$$

Constraint (30) indicates the minimum and maximum amounts of wind power output. The generation companies (GENCOs) production limits and the CAES capacity constraint are given in constraints (31), (32), respectively.

$$\mathrm{P}^{\mathrm{Wind,min}}_{w} \leq p^{\mathrm{Wind}}_{s,t,w} \leq \mathrm{P}^{\mathrm{Wind,max}}_{w}, \forall\, s, \forall\, t, \forall\, w \tag{30}$$

$$\mathrm{P}^{\mathrm{Gen,min}}_{i} \leq p^{\mathrm{Gen}}_{s,t,i} \leq \mathrm{P}^{\mathrm{Gen,max}}_{i}, \forall\, s, \forall\, t, \forall\, i \tag{31}$$

$$\mathrm{P}^{\mathrm{CAES,min}}_{k} \leq p^{\mathrm{CAES}}_{s,t,k} \leq \mathrm{P}^{\mathrm{CAES,max}}_{k}, \forall\, s, \forall\, t, \forall\, k \tag{32}$$

3.3. Second stage (SCUC with CAES)

The stochastic SCUC problem varies from one scenario to another one because of changing in the values of uncertain parameters. The certain value of operating and spinning reserves are considered to preserve the security of the system when the power outage happens or hourly demand raises suddenly. In the stochastic SCUC problem modelling, each possible state of the system is indicated by a scenario in which equipment outages and possible load grows are considered in the SCUC solution then reserve limits are relaxed. The objective function of the proposed stochastic SCUC problem has been expressed as follow:

$$\min \sum_{s=1}^{NS} \rho_{s} \sum_{t=1}^{NT} \begin{Bmatrix} \displaystyle\sum_{i=1}^{NG} (\mathrm{F}^{\mathrm{c}}_{i}(p^{\mathrm{Gen}}_{s,t,i} \times g_{s,t,i}) + \mathrm{SUC}_{s,t,i} + \mathrm{SDC}_{s,t,i}) \\ + \displaystyle\sum_{w=1}^{NW} (p^{\mathrm{Wind}}_{s,t,w} \times \mathrm{K}^{\mathrm{Wind}}) + \sum_{l=1}^{NL} (p^{\mathrm{Loss}}_{s,t,l} \times \mathrm{K}^{\mathrm{Loss}}) \\ + \displaystyle\sum_{k=1}^{NCAES} (\mathrm{F}^{c}_{k}(p^{\mathrm{CAES}}_{s,t,k} \times g_{s,t,k})) + \boldsymbol{C_{DR}} \end{Bmatrix} \tag{33}$$

The objective function of the second stage is composed of thermal generation cost including fuel, start-up and shutdown costs of individual units, wind power system operation cost, power losses cost, CAES units operation cost along with DR sources cost over the scheduling horizon. The stochastic SCUC problem subjected to the several constraints is listed as follow. Eq. (34) represents energy power balance, constraints (35) and (36) shows require spinning and non-spinning reserve limits, respectively. Constraints (37) and (38) demonstrates the limits of the regulation up/down, respectively. Ramping up/down limits are given in constraints (39) and (40), respectively. Eqs. (41), (42) show the minimum up and down time constraints. Constraints (43)-(44) depict the fuel and emission limits. Finally, the network security limits involving both transmission flow and bus voltage are restricted by (45)-(46).

$$\sum_{i=1}^{NG} (p_{s,t,i}^{\text{Gen}} \times g_{s,t,i}) + \sum_{w=1}^{NW} p_{s,t,w}^{\text{Wind}} = p_{s,t}^{\text{D}} + p_{s,t,l}^{\text{Loss}}, \ \forall\ t, \forall\ s \tag{34}$$

$$\sum_{i=1}^{NG} (sr_{s,t,i} \times g_{s,t,i}) + \sum_{k=1}^{NCAES} (sr_{s,t,k} \times g_{s,t,k}) \geq \text{R}_t^S, \forall\ t, \forall\ s \tag{35}$$

$$\sum_{i=1}^{NG} (nr_{s,t,i} \times g_{s,t,i}) + \sum_{k=1}^{NCAES} (nr_{s,t,k} \times g_{s,t,k}) \geq \text{R}_t^N, \forall\ t, \forall\ s \tag{36}$$

$$\sum_{i=1}^{NG} (ru_{s,t,i} \times g_{s,t,i}) + \sum_{k=1}^{NCAES} (ru_{s,t,k} \times g_{s,t,k}) \geq \text{R}_t^{ru}, \forall\ t, \forall\ s \tag{37}$$

$$\sum_{i=1}^{NG} (rd_{s,t,i} \times g_{s,t,i}) + \sum_{k=1}^{NCAES} (rd_{s,t,k} \times g_{s,t,k}) \geq \text{R}_t^{rd}, \forall\ t, \forall\ s \tag{38}$$

$$\begin{aligned} p_{s,t+1,i} - p_{s,t,i} \leq {} & [1 - g_{s,t+1,i}(1 - g_{s,t,i})]\text{RU}_i \\ & + [g_{s,t+1,i}(1 - g_{s,t,i})\text{P}_i^{\min}], \quad \forall\ t, \forall\ s, \forall\ i \end{aligned} \tag{39}$$

$$\begin{aligned} p_{s,t,i} - p_{s,t+1,i} \leq {} & [1 - g_{s,t,i}(1 - g_{s,t+1,i})]\text{RD}_i \\ & + [g_{s,t,i}(1 - g_{s,t+1,i})\text{P}_i^{\min}], \quad \forall\ t, \forall\ s, \forall\ i \end{aligned} \tag{40}$$

$$\text{UT}_i = \max\{0, \min\{T, (\text{MU}_i - \text{TU}_{i,0})g_{s,i,0}\}\}, \quad \forall\ i, \forall\ s \tag{41}$$

$$\text{DT}_i = \max\{0, \min\{T, (\text{MD}_i - \text{TD}_{i,0})(1 - g_{s,i,0})\}\}, \quad \forall\ i, \forall\ s \tag{42}$$

$$F_{FT}^{\min} \leq \sum_{s=1}^{NS} \sum_{t=1}^{NT} \left\{ \begin{aligned} & \sum_{i \in FT} (\text{F}_i^f(p_{s,t,i}^{\text{Gen}} \times g_{s,t,i}) + \text{SUC}_{s,t,i}^f + \text{SDC}_{s,t,i}^f) \\ & + \sum_{k}^{NCAES} (\text{F}_k^f(p_{s,t,k}^{\text{CAES}} \times g_{s,t,k})) \end{aligned} \right\} \leq F_{FT}^{\max} \tag{43}$$

$$\begin{aligned} \sum_{s=1}^{NS} \sum_{t=1}^{NT} \Bigg\{ & \sum_{i=1}^{NG} (\text{F}_i^e(p_{s,t,i}^{\text{Gen}} \times g_{s,t,i}) + \text{SUC}_{s,t,i}^e + \text{SDC}_{s,t,i}^e) \\ & + \sum_{k}^{NCAES} (\text{F}_k^e(p_{s,t,k}^{\text{CAES}} \times g_{s,t,k})) \Bigg\} \leq E_S^{\max} \end{aligned} \tag{44}$$

$$\text{P}_l^{\text{Flow,min}} \leq p_{s,t,l}^{\text{Flow}} \leq \text{P}_l^{\text{Flow,max}}, \forall\ t, \forall\ s, \forall\ l \tag{45}$$

$$\text{V}_b^{\min} \leq v_{s,t,b} \leq \text{V}_b^{\max}, \quad \forall\ t, \forall\ s, \forall\ b \tag{46}$$

4. Stochastic chance constrained programming

Commonly, uncertainties can be separated into external uncertainties as the price of feed, recycle flows, connected operating units temperature, raw material supply, the consumption demand of consumers, market situations and internal uncertainties that introduce process knowledge unavailability like model parameters (Gautam & Mithulananthan, 2007). Uncertain variables may be dependent or independent and their stochastic distribution may have various status. Often normal distribution is taken into account as a sufficient assumption for many uncertain variables in the engineering workout (Gazijahani & Salehi, 2017). The amounts of mean and variance are usually accessible. Nevertheless, the suggested uncertain variables will propagate via the procedure to the output variables and thus the outputs will be uncertain. For a non-linear process, it is hard to define the outputs distribution. Because of this mentioned reason, we use chance constrained programming (CCP) that is explained in continue.

The main advantage of the CCP, which presented by charnes and cooper (Charnes & Cooper, 1959) for the first time, is the solving of the non-linear optimization problems with uncertainties contained in constraints as well as objective function by converting stochastic constraints to the deterministic tantamount with respect to the predetermined confidence level. The CCP is an optimization problem that ensures that the probability of meeting a specified constraint is above a specified level. On the other hands, it limits the possible zone until the confidence level would be high. In order to deal with the uncertainties in the proposed problem, the general model of chance constrained stochastic problem is formulated as follows (Adam, Branda, Heitsch, & Henrion, 2018; Arnold, Henrion, Möller, & Vigerske, 2013; Farshbaf-Shaker, Henrion, & Hömberg, 2018; Salyani et al., 2018; Van Ackooij, Zorgati, Henrion, & Möller, 2011):

$$\min_{x \in X}\ F(x) \tag{47}$$

Subject to

$$\Pr\{G(x, \xi) \leq 0\} \geq 1 - \varepsilon \tag{48}$$

Where $X \subset \mathfrak{R}^n$ presents the deterministic feasible zone, $F(x)$ denotes the objective amount to be minimized, ξ is a random vector whose probability distribution is supported on set $\Xi \subset \mathfrak{R}^d$, $G\colon\ \mathfrak{R}^n \times \mathfrak{R}^d \to \mathfrak{R}^m$ is a constraint mapping, 0 is an m-dimensional vector of zeros, and $\varepsilon \in (0, 1)$ is given and usually named the risk level of the chance-constrained optimization. This method will minimize the objective function over a deterministic feasible set while $G(x, \xi) \leq 0$ should be satisfied with a probability of at least $1 - \varepsilon$. It should be mentioned that in this paper the proposed CCP has been applied to the active power balance constraint, since it ensures that the probability of load imbalance is less than a predefined risk level.

4.1. Two-stage stochastic programming

An innovative two-stage model has been suggested for decision making in an uncertain environment. In this method, the decision variables are divided into two main groups, "*here-and-now*" and "*wait-and-see*". In the suggested problem, the decision variables of the first stage are the amount of LMP, the dispatch of thermal units considering the short-term deterministic prediction of wind power generation, and charging/discharging planning of CAES. While the decision variables of the second stage are the DR actions and re-dispatching of thermal units for satisfying all operational constraints under the uncertainty of wind power generation.

Dual variables d and variables c (like wind production and…) are taken into account as the first stage that should be decided "*here-and-now*" prior to the resolution of uncertainty and operational variables x_t that are "*wait-and-see*" variables and binary variables b in the second stage, which can be decided when all uncertain parameters have been observed. It is a typical two-stage problem, which is usually addressed using the two-stage stochastic programming approach (Zhou, Zhang, & Liu, 2013). The two-stage stochastic programming problem used in this work is formulated as follow:

$$\begin{aligned} & (\text{First\_stage}):\ \max_{c,d} \quad F_f(c, d) + E[F_f(c, d, \xi)] \\ & \text{S.t.}\Phi_f(\text{c,d}) = 0 \\ & \Psi_f(c, d) \leq 0 \\ & c \in \mathfrak{R}^1 \end{aligned} \tag{49}$$

$$\begin{aligned} & (\text{Second\_stage}):\ F_s(c, d, \xi) = \min_{x_t} \quad F_s(b, c, d, x_t, \xi) \\ & \text{S.t.}\Phi_s(b, c, d, x_t, \xi) = 0 \\ & \Psi_s(b, c, d, x_t, \xi) \leq 0 \\ & b \in \{0, 1\}^m, \ \ x_t \in \mathfrak{R}^n \end{aligned} \tag{50}$$

Where, the objective function is split into a deterministic term F_f representing decisions and the expectation of a stochastic term F_s, which depends on the realization of uncertain parameters n at the operation stage (second stage). The proposed method is applied considering operational flexibility as an important feature to accommodate renewable energy into the power systems. There are different metrics to assess the flexibility of power systems such as power capacity for up/down power regulation, power ramp rate, storage energy and ramp duration, which in this paper power capacity for up/down power regulation is utilized.

The flowchart of the proposed method is graphically shown in Fig. 1. After entering the data of wind turbine, GENCOs, network, load profile and storage, the multi-period OPF have been implemented to obtain the LMPs value, voltage profile, power losses at different buses as well as power transaction at each line and between areas. Moreover, the optimal CAES charging/discharging, optimal production of wind turbine, generation re-dispatching achieved from this program running. Then the two-stage stochastic program is extended with the aim of congestion alleviating (i.e., aimed at maximizing social welfare) at first stage and wind power curtailment minimization by co-optimization scheduling of CAES and DRP at second stage. The CCP utilized to harness the risk due to fluctuations of wind power generation. Finally, this program updates in each iteration (run for 24 h and three scenarios) and the best results will be attained.

5. Results and discussions

5.1. Case study

The proposed two-stage problem has been implemented on the modified IEEE 30-bus test system with three regions (Shayesteh, Gayme, & Amelin, 2018). The topology of the system is shown in Fig. 2 that include six generator buses, twenty load buses, and forty interconnected branches. In addition, six WTs and six CAESs have been already installed in the network and exploited. The generators operation factors (Olamaei, Nazari, & Bahravar, 2018) and the parameters related to CAES (Gu, McCalley, Ni, & Bo, 2013) presented in Tables 1 and 2, respectively. The network load profile and wind speed data are derived from references Gazijahani, Ravadanegh, and Salehi (2018) and (National Wind & solar Technology Center, 2017), respectively. The proposed model has been implemented in MATLAB software environment running on a laptop with Intel(R) Core(TM) i5-4300 M CPU @ 2.60 GHz and 8 GB RAM. Also, the total CPU time to run the problem is 14.76 s which is compatible with such a large scale complex problem.

To illustrate the impact of geographical distribution of CAES and DR on the problem, the simulation results have been implemented under different cases:

- **Case I:** Without CAES and DRP
- **Case II:** Only CAES is employed
- **Case III:** Both CAES and DRP are employed

The hourly load profile with and without implementing DRP is shown in Fig. 3 for the test system under study. As can be observed from the figure, the DR program is compared in different participation factors of demand. The results prove that if customers actively participate in RTP, this program can reduce and shift the load effectively and improves it. Optimal RTP, which are acceptable for both the utility and customers, can be achieved by this interactive process. In general, the DR program is applied to decrease costs, alleviate congestion, and improve load curve specifications. During the peak hours, power transaction can be reached to its maximum amount in lines and congestion occurred. When congestion occurred in the network, the power of cheaper units may not be fully used, which will increase and create different LMP in different busses. The LMP is shown in Fig. 4 for all network busses at the selected hour in different cases. As seen from the figure the suggested integrated method based on optimal participation of CAES and DRP makes the nodal prices smoother than two other cases. The proposed method, in addition to reducing network congestion, also increases the system social welfare compared to the case, which CAES and DRP operate individually.

Hourly power produced and consumed of the CAES is shown in Fig. 5. Each column of the plot illustrates the sum of pumped/injected air to/from CAES, which depends on the equilibrium equation and the LMP. If the answer of the equilibrium equation is negative, and the charging price is lower than wind turbines production and generators generation cost, the CAES will be charged. However, the answer of the equilibrium equation is positive, and the discharging price is lower than the wind turbines production and generators generation cost, the CAES will be discharged. With this work, the LMP at different buses reduced and congestion of the network managed. As mentioned, the CAES plays a more active role in reducing the LMP through discharging on the critical hours (i.e., peak hours). During these hours, the LMP can be reduced greatly through providing the demand of consumers by CAES discharging. Conversely, in the off-peak hours where the LMP is low, the CAES can be charged to re-enter the network when needed.

As displayed in Table 3, the amount of generators re-dispatching in the presence of CAES and DRP is considerably less than two other cases. This concept guarantees that CAES and DRP will operate collaboratively at a lower cost and the results are more acceptable. The DRP transfers peak load of system to off-peak periods (as given in Fig. 3) and optimal scheduling of CAES (as shown in Fig. 5) causes to modify the pattern of power flow, which are, alleviate the congestion of lines in the network. The lines power flow at peak hour is illustrated in Fig. 6 in different cases. As can be seen, using CAES and DRP have a great impact on limiting the amount of power transaction in the overloaded lines. This is due to the participation of customers in DRP for decreasing their consumption and changing the power flow to low load lines. Another result that can be subtracted from Fig. 6 is that the suggested integrated approach has a better impact on the CM of the system compared to the separate use of them. It can also be concluded that the CAES acts as a backup source for wind turbines.

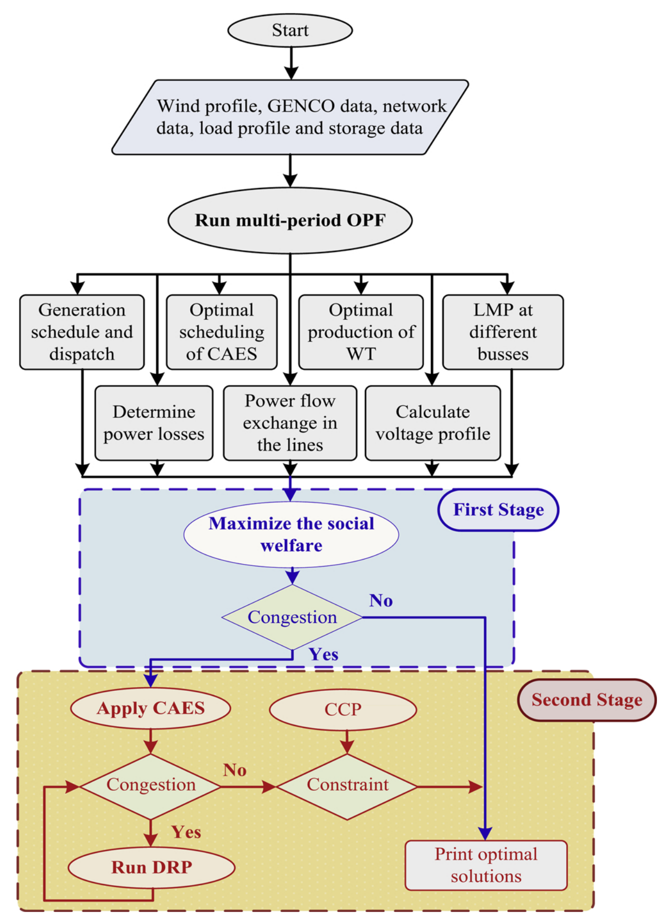

Fig. 1. Outline of the proposed algorithm.

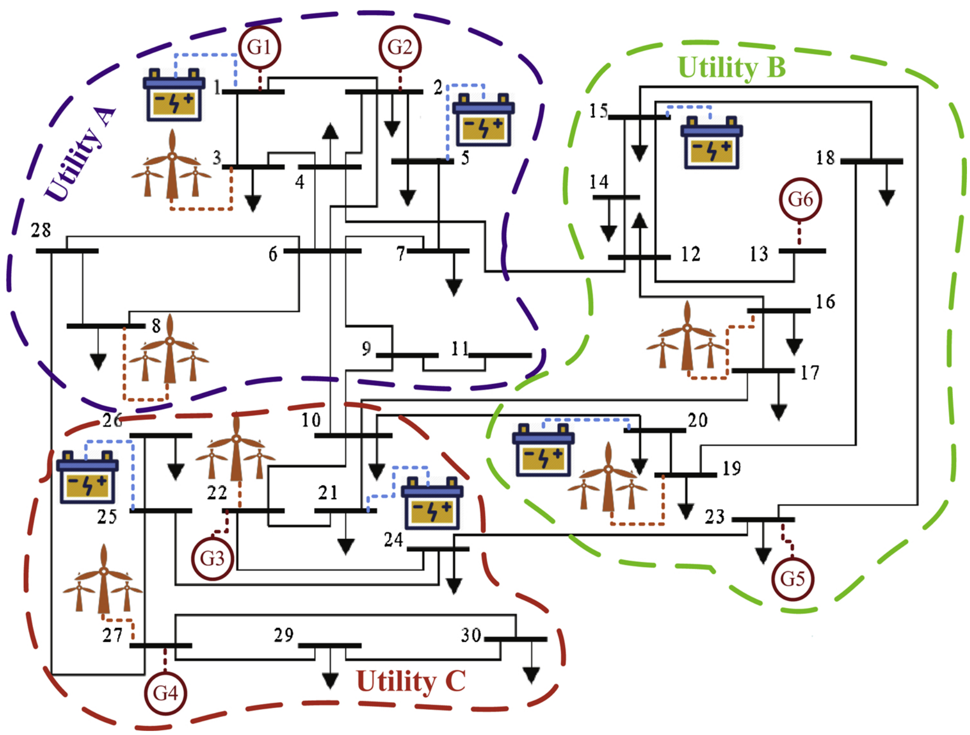

Fig. 2. Modified IEEE 30-bus test system with three area.

Table 1
Generator data.

Area	Bus number	Cost Coefficients			P^{min} [MW]	P^{min} [MW]	$P_0(i)$ [MW]	Q^{min} [MVar]	Q^{max} [MVar]	MDT (hr.)	MUT (hr.)	RD [MW]	RU [MW]	SDC ($)	SUC ($)
		a(i)	b(i)	c(i)											
Utility A	1	0	2	0.02	0	80	23.54	−20	150	10	10	50	50	0	440
	2	0	1.75	0.0175	0	80	60.97	−20	60	10	10	50	50	0	440
Utility B	13	0	3	0.025	0	40	37.00	−15	44.7	1	1	30	30	0	100
	23	0	3	0.025	0	30	19.20	−10	40	1	1	25	25	0	100
Utility C	22	0	1	0.0625	0	50	21.59	−15	62.5	1	1	30	30	0	100
	27	0	3.25	0.00834	0	55	26.91	−15	26.91	1	1	25	25	0	100

Table 2
Parameters of CAES.

Area	Bus No.	A_{min} [MWh]	A_{max} [MWh]	$N^{w,\ min}$ [MW]	$N^{w,\ max}$ [MW]	$N^{inj,\ min}$ [MW]	$N^{inj,\ min}$ [MW]	η^{w}	η^{inj}
Utility A	1	40	100	5	30	5	30	0.95	0.95
	5	25	70	3	20	3	20	0.95	0.95
Utility B	15	40	100	5	30	5	30	0.95	0.95
	20	30	80	4	25	4	25	0.95	0.95
Utility C	21	25	70	3	20	3	20	0.95	0.95
	25	40	100	5	30	5	30	0.95	0.95

The power generation of different generators over operation horizon is presented in Fig. 7, which the output power of generators change in the presence of WTs, CAESs, and DR sources. The hourly WTs output depicts in Fig. 8 that each column shows the sum of all wind turbines production. The optimal output of wind turbines determined by solver in presences of generators generation and CAES scheduling. Notice that in the suggested method, wind power outputs are operated at their maximum capacity to reach the maximum possible profit at the minimum cost.

Fig. 9 compares the power losses in both initial (without CAES and DRP) and secondary (with CAES and DRP) cases. As can be seen, the system power losses have dropped dramatically with the addition of the CAES and DRP. The voltage profile of the system shown in Fig. 10, which the initial voltage magnitude in each bus significantly improved (smoothed) in comparison to the case with CAES and implementing DRP. Both Figs. 9 and 10 demonstrate that the suggested method not only alleviates the congestion of network but also improves the system technical characteristics such as power losses and voltage profile. Moreover, Table 4 shows the results of second stage at different scenarios.

6. Conclusion

This paper proposed a methodology for CM of wind integrated transmission network by generators re-dispatch, scheduling of CAES units and implementing DRP. For this purpose, a chance constraint two-stage stochastic program was developed to maximize the social welfare of the whole system with the goal of congestion alleviation as well as minimize the system operation cost. The DRP, by creating different tariffs for electricity price over different hours, encourages consumers

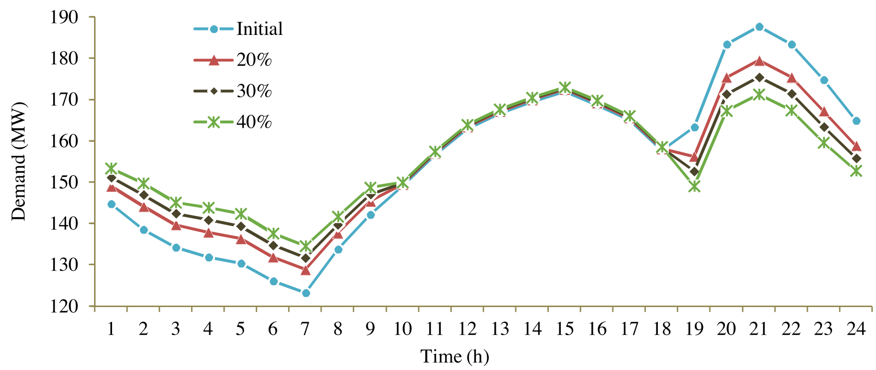

Fig. 3. Daily system's load profile with and without DRP in different participation factors.

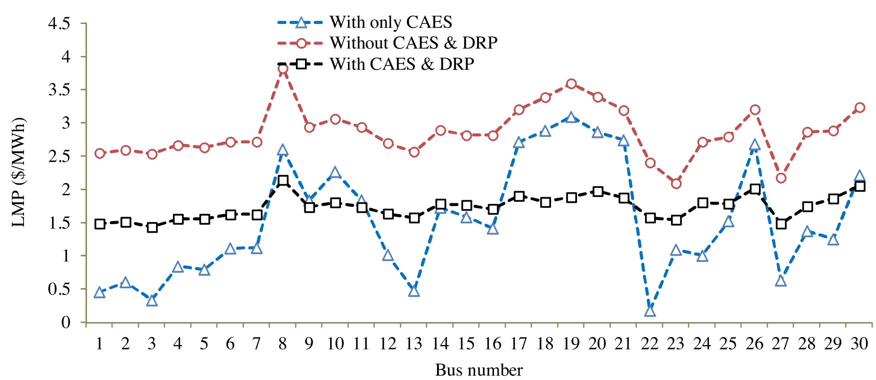

Fig. 4. The LMPs value at hour 23 in different busses.

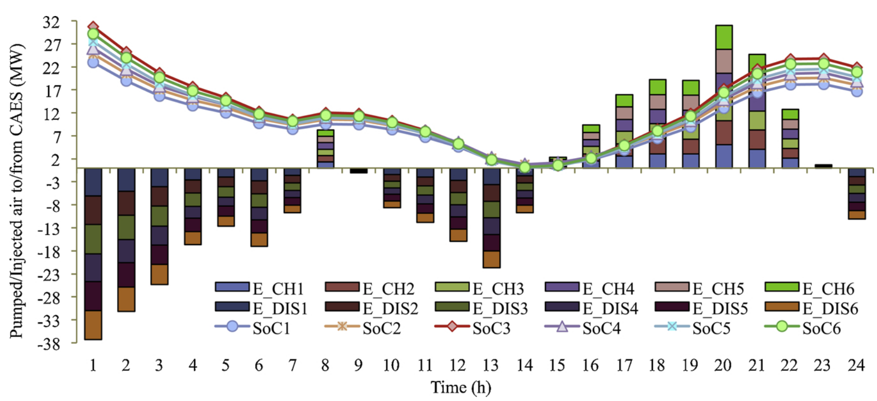

Fig. 5. Optimal day ahead arbitrage of CAES.

Table 3
Results of generators re-dispatching (MW).

Gen. number	Without CAES & DRP	With only CAES	With CAES & DRP
1	44.73	33.55	25.14
2	58.26	39.69	29.99
3	22.31	21.15	17.64
4	32.33	18.13	14.24
5	15.78	11.46	9.64
6	15.78	16.76	13.28

to change their energy consumption plans, thereby reducing the network congestion. The numerical and simulation results have indicated that the co-optimization CAES and DRP reduce the congestion cost, alleviate the uncertainty and increase the penetration of wind powers, and finally maximize the social welfare amount in comparison with other cases. It can be seen that the proposed method not only expresses the mentioned results, but also improves some technical specifications of the system, such as system power losses, and voltage profile. Also, proper scheduling of the CAESs can reduce the effect of wind generation uncertainty on the conventional generation units' dispatch and improve the voltage profile.

Based on results, the following issues are achieved.

i Using DRP and CAES could maximize the social welfare and minimize the operation costs of the system.
ii Applying CCP can harness the uncertainty of wind power generation.
iii Two-stage problem modelling was proposed to alleviate the congestion and smooth LMPs at different nodes.
iv Wind output curtailment can be appropriately reduced by utilizing CAES and DRP.
v Technical characteristics of the system such as voltage profile and power losses are improved.
vi Re-dispatching of generators is needed in the presence of CAES to find optimal production of GENCOs.

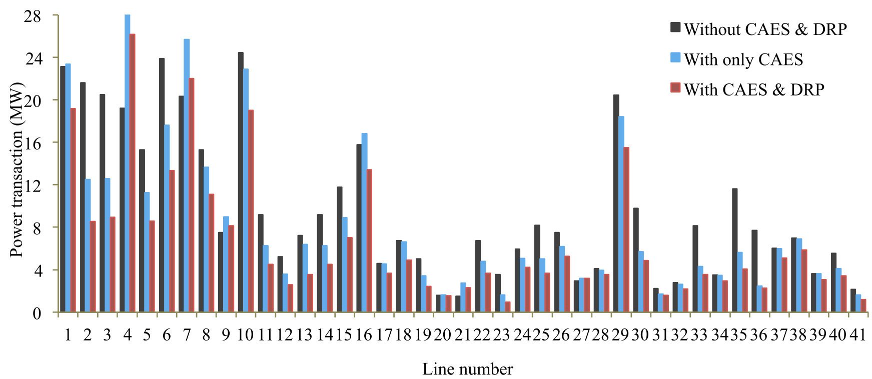

Fig. 6. Congestion analysis in different cases.

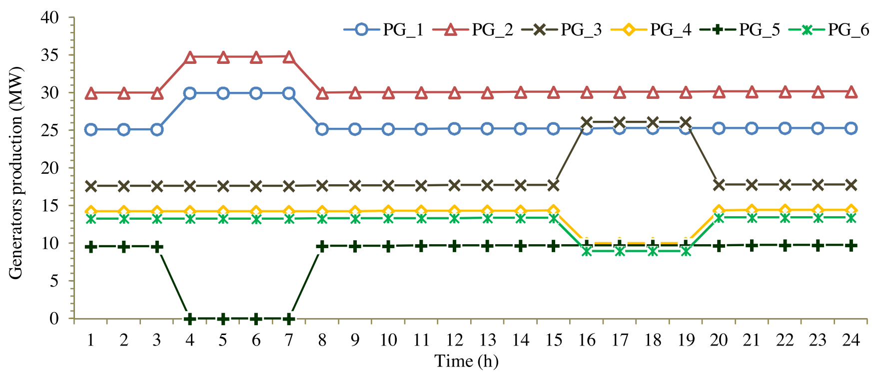

Fig. 7. Power generation of different generators over operation horizon.

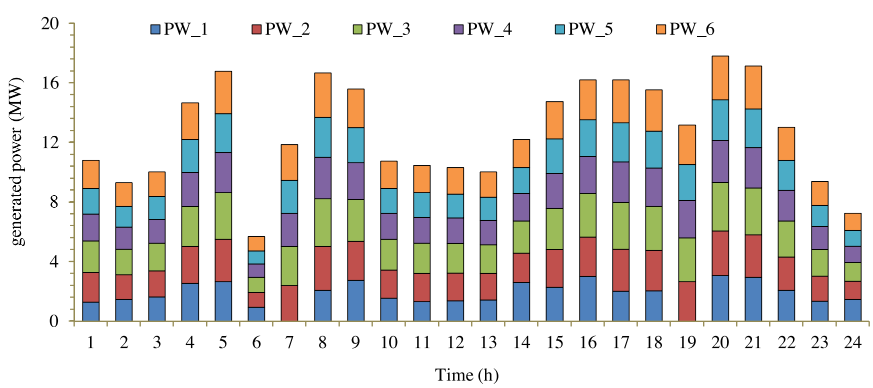

Fig. 8. Hourly generated power of wind producers.

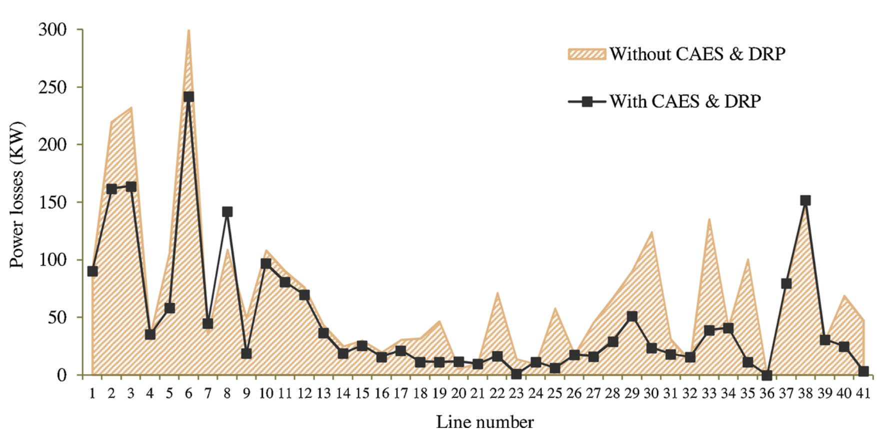

Fig. 9. Power losses of network.

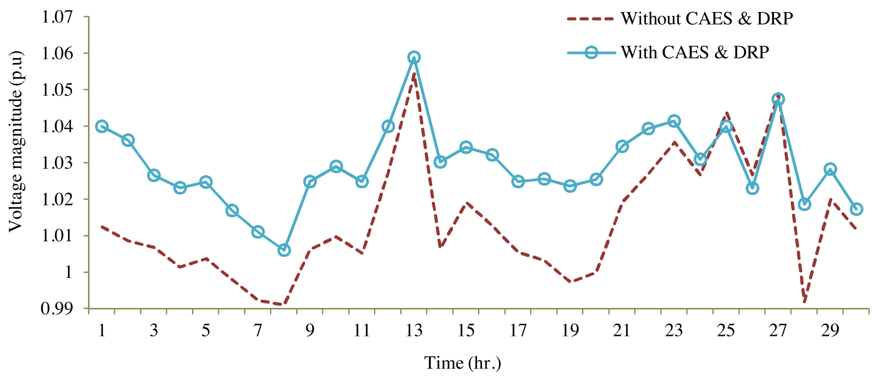

Fig. 10. Voltage profile of system.

Table 4
Results of second stage (SCUC with CAES and DRP).

	Scenario 1	Scenario 2	Scenario 3
Total cost ($)	7949.1353	7422.0584	7265.3921

References

Aazami, R., Aflaki, K., & Haghifam, M. R. (2011). A demand response based solution for LMP management in power markets. *International Journal of Electrical Power & Energy Systems, 33*(5), 1125–1132 Jun 1.

Abdolahi, A., Salehi, J., Gazijahani, F. S., & Safari, A. (2018). Probabilistic multi-objective arbitrage of dispersed energy storage systems for optimal congestion management of active distribution networks including solar/wind/CHP hybrid energy system. *Journal of Renewable and Sustainable Energy, 10*(4), 045502 Jul 22.

Adam, L., Branda, M., Heitsch, H., & Henrion, R. (2018). Solving joint chance constrained problems using regularization and benders' decomposition. *Annals of Operations Research,* 1–27 Jul 16.

Aghaei, J., Alizadeh, M. I., Abdollahi, A., & Barani, M. (2016). Allocation of demand response resources: Toward an effective contribution to power system voltage stability. *IET Generation Transmission & Distribution, 10*(16), 4169–4177 Dec 8.

Ansari, M. R., Amjady, N., & Vatani, B. (2014). Stochastic security-constrained hydro-thermal unit commitment considering uncertainty of load forecast inflows to reservoirs and unavailability of units by a new hybrid decomposition strategy. *IET Generation Transmission & Distribution, 8*(12), 1900–1915 Dec 1.

Arnold, T., Henrion, R., Möller, A., & Vigerske, S. A. (2013). *Mixed-integer stochastic nonlinear optimization problem with joint probabilistic constraints.* Humboldt-Universität zu Berlin, Mathematisch-Naturwissenschaftliche Fakultät II, Institut für Mathematik May 14.

Attarha, A., Amjady, N., Dehghan, S., & Vatani, B. (2018). Adaptive robust self-scheduling for a wind producer with compressed air energy storage. *IEEE Transactions on Sustainable Energy* Feb 15.

Charnes, A., & Cooper, W. W. (1959). Chance-constrained programming. *Management Science, 6*(1), 73–79 Oct.

Cleary, B., Duffy, A., OConnor, A., Conlon, M., & Fthenakis, V. (2015). Assessing the economic benefits of compressed air energy storage for mitigating wind curtailment. *IEEE Transactions on Sustainable Energy, 6*(3), 1021–1028 Jul.

Conejo, A. J., Milano, F., & García-Bertrand, R. (2006). Congestion management ensuring voltage stability. *IEEE Transactions on Power Systems, 21*(1), 357–364 Feb.

Dash, S. N., Padhi, R. K., Dora, T., Surendar, A., & Cristan, K. (2019). A robust optimization method for bidding strategy by considering the compressed air energy storage. *Sustainable Cities and Society*101564 Apr 24.

Dehnavi, E., & Abdi, H. (2017). Determining optimal buses for implementing demand response as an effective congestion management method. *IEEE Transactions on Power Systems, 32*(2), 1537–1544 Mar.

Farshbaf-Shaker, M. H., Henrion, R., & Hömberg, D. (2018). Properties of chance constraints in infinite dimensions with an application to pde constrained optimization. *Set-Valued and Variational Analysis, 26*(4), 821–841 Dec 1.

Fernández-Blanco, R., Dvorkin, Y., & Ortega-Vazquez, M. A. (2017). Probabilistic security-constrained unit commitment with generation and transmission contingencies. *IEEE Transactions on Power Systems, 32*(1), 228–239 Jan 1.

Gautam, D., & Mithulananthan, N. (2007). Locating distributed generator in the LMP-based electricity market for social welfare maximization. *Electric Power Components and Systems, 35*(5), 489–503 May 1.

Gazijahani, F. S., & Salehi, J. (2017). Stochastic multi-objective framework for optimal dynamic planning of interconnected microgrids. *IET Renewable Power Generation, 11*(14), 1749–1759.

Gazijahani, F. S., & Salehi, j. (2018a). Robust design of microgrids with reconfigurable topology under severe uncertainty. *IEEE Transactions on Sustainable Energy, 9*(2), 559–569.

Gazijahani, F. S., & Salehi, J. (2018b). Reliability constrained two-stage optimization of multiple renewable-based microgrids incorporating critical energy peak pricing demand response program using robust optimization approach. *Energy, 161*, 999–1015 Oct 15.

Gazijahani, F. S., & Salehi, J. (2018c). Game theory based profit maximization model for microgrid aggregators with presence of EDRP using information gap decision theory. *IEEE Systems Journal, 99*, 1–9.

Gazijahani, F. S., Ravadanegh, S. N., & Salehi, J. (2018). Stochastic multi-objective model for optimal energy exchange optimization of networked microgrids with presence of renewable generation under risk-based strategies. *ISA Transactions, 73*, 100–111 Feb 1.

Ghaljehei, M., Ahmadian, A., Golkar, M. A., Amraee, T., & Elkamel, A. (2018). Stochastic SCUC considering compressed air energy storage and wind power generation: A techno-economic approach with static voltage stability analysis. *International Journal of Electrical Power & Energy Systems, 100*, 489–507 Sep 30.

Gu, Y., McCalley, J., Ni, M., & Bo, R. (2013). Economic modeling of compressed air energy storage. *Energies, 6*(4), 2221–2241 Apr.

Hazra, J., & Sinha, A. K. (2007). Congestion management using multiobjective particle swarm optimization. *IEEE Transactions on Power Systems, 22*(4), 1726–1734 Nov.

Heydarian-Forushani, R., Golshan, M. H., Moghaddam, M. P., Shafie-Khah, M., & Catalão, J. P. S. (2015). Robust scheduling of variable wind generation by coordination of bulk energy storages and demand response. *Energy Conversion and Management, 106*, 941–950 Dec 1.

Kargarian, A., Raoofat, M., & Mohammadi, M. (2011). Reactive power market management considering voltage control area reserve and system security. *Applied Energy, 88*(11), 3832–3840 Nov 1.

Khodaei, A., Shahidehpour, M., & Bahramirad, S. (2011). SCUC with hourly demand response considering intertemporal load characteristics. *IEEE Transactions on Smart Grid, 2*(3), 564–571 Sep.

Kumar, A., Srivastava, S. C., & Singh, S. N. (2005). Congestion management in competitive power market: A bibliographical survey. *Electric Power Systems Research, 76*(1–3), 153–164 Sep 1.

Liu, W., Wu, Q., Wen, F., & Østergaard, J. (2014). Day-ahead congestion management in distribution systems through household demand response and distribution congestion prices. *IEEE Transactions on Smart Grid, 5*(6), 2739–2747 Nov.

Lund, H., & Salgi, G. (2009). The role of compressed air energy storage (CAES) in future sustainable energy systems. *Energy Conversion and Management, 50*(5), 1172–1179 May 1.

Moradi, M. H., Reisi, A. R., & Hosseinian, S. M. (2018). An optimal collaborative congestion management based on implementing DR. *IEEE Transactions on Smart Grid, 9*(5), 5323–5334 Sep.

National Wind and solar Technology Center (2017). *National renewable energy laboratory [Online].* March. 24. Available http:// www.nrel.gov/midc/nwtc_m2/.

Nikoobakht, A., & Aghaei, J. (2016). IGDT-based robust optimal utilisation of wind power generation using coordinated flexibility resources. *IET Renewable Power Generation, 11*(2), 264–277.

Nikoobakht, A., Aghaei, J., Shafie-Khah, M., & Catalão, J. P. S. (2018). Interval based robust chance constrained allocation of demand response programs in wind integrated power systems. *IET Renewable Power Generation,* 1–10.

Olamaei, J., Nazari, M. E., & Bahravar, S. (2018). Economic environmental unit commitment for integrated CCHP-thermal-heat only system with considerations for valve-point effect based on a heuristic optimization algorithm. *Energy, 159*, 737–750 Sep 15.

Roscoe, A., & Ault, G. (2010). Supporting high penetrations of renewable generation via implementation of real-time electricity pricing and demand response. *IET Renewable Power Generation, 4*(4), 369–382.

Salehizadeh, M. R., Rahimi-Kian, A., & Oloomi-Buygi, M. (2015). Security-based multi-objective congestion management for emission reduction in power system. *International Journal of Electrical Power & Energy Systems, 65*, 124–135 Feb 1.

Salyani, P., Salehi, J., & Gazijahani, F. S. (2018). Chance constrained simultaneous optimization of substations, feeders, renewable and non-renewable distributed generations in distribution network. *Electric Power Systems Research, 158*, 56–69 May 31.

Seyyedeh-Barhagh, S., Majidi, M., Nojavan, S., & Zare, K. (2019). Optimal scheduling of hydrogen storage under economic and environmental priorities in the presence of renewable units and demand response. *Sustainable Cities and Society, 46*, 101406 Apr 1.

Shafiee, S., Zareipour, H., Knight, A. M., Amjady, N., & Mohammadi-Ivatloo, B. (2017).

Risk-constrained bidding and offering strategy for a merchant compressed air energy storage plant. *IEEE Transactions on Power Systems, 32*(2), 946–957 Mar.
Shafie-Khah, M., Moghaddam, M. P., & Sheikh-El-Eslami, M. K. (2011). Unified solution of a non-convex SCUC problem using combination of modified branch-and-bound method with quadratic programming. *Energy Conversion and Management, 52*(12), 3425–3432 Nov 1.
Shafie-Khah, M., Moghaddam, M. P., Sheikh-El-Eslami, M. K., & Catalão, J. P. (2014). Fast and accurate solution for the SCUC problem in large-scale power systems using adapted binary programming and enhanced dual neural network. *Energy Conversion and Management, 78*, 477–485 Feb 1.
Shao, C., Wang, X., Shahidehpour, M., Wang, X., & Wang, B. (2017). Security-constrained unit commitment with flexible uncertainty set for variable wind power. *IEEE Transactions on Sustainable Energy, 8*(3), 1237–1246 Jul.
Shayesteh, E., Gayme, D. F., & Amelin, M. (2018). System reduction techniques for storage allocation in large power systems. *International Journal of Electrical Power & Energy Systems, 95*, 108–117 Feb 1.
Tejada-Arango, D. A., Sánchez-Martın, P., & Ramos, A. (2018). Security constrained unit commitment using line outage distribution factors. *IEEE Transactions on Power Systems, 33*(1), 329–337 Jan.
Van Ackooij, W., Zorgati, R., Henrion, R., & Möller, A. (2011). *Chance constrained programming and its applications to energy management. Stochastic optimization-Seeing the optimal for the Uncertain*. IntechOpen Feb 28.
Wang, Q., Wang, J., & Guan, Y. (2013). Stochastic unit commitment with uncertain demand response. *IEEE Transactions on Power Systems, 28*(1), 562–563 Feb 1.
Wei, Y., Li, F., & Tomsovic, K. (2012). Measuring the volatility of wholesale electricity prices caused by wind power uncertainty with a correlation model. *IET Renewable Power Generation, 6*(5), 315–323.
Yang, S., Zeng, D., Ding, H., Yao, J., Wang, K., & Li, Y. (2016). Stochastic security-constrained economic dispatch for random responsive price-elastic load and wind power. *IET Renewable Power Generation, 10*(7), 936–943.
Yousefi, A., Nguyen, T. T., Zareipour, H., & Malik, O. P. (2012a). Congestion management using demand response and FACTS devices. *International Journal of Electrical Power & Energy Systems, 37*(1), 78–85 May 1.
Yousefi, A., Nguyen, T. T., Zareipour, H., & Malik, O. P. (2012b). Congestion management using demand response and FACTS devices. *International Journal of Electrical Power & Energy Systems, 37*(1), 78–85 May 1.
Zaeim-Kohan, F., Razmi, H., & Doagou-Mojarrad, H. (2018). Multi-objective transmission congestion management considering demand response programs and generation rescheduling. *Applied Soft Computing, 70*, 169–181 Sep 1.
Zhang, J., Zhang, P., Wu, H., Qi, X., Yang, S., & Li, Z. (2018). Two-stage load-scheduling model for the incentive-based demand response of industrial users considering load aggregators. *IET Generation Transmission & Distribution* May 17.
Zhao, C., Wang, J., Watson, J. P., & Guan, Y. (2013). Multi-stage robust unit commitment considering wind and demand response uncertainties. *IEEE Transactions on Power Systems, 23*(3), 2708–2717 Aug.
Zhou, Z., Zhang, J., Liu, P., Li, Z., Georgiadis, M. C., & Pistikopoulos, E. N. (2013). A two-stage stochastic programming model for the optimal design of distributed energy systems. *Applied Energy, 103*, 135–144 Mar 1.